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IMPACT OF HIGH FREQUENCY TRADING ON THE VOLATILITY OF BSE – OLS APPROACH

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ABSTRACT

Purpose:

HFTs' most problematic issue is market volatility. It quantifies the risk of a security's value change. When volatility is strong, an asset's value may move throughout a wider price range. The standard deviation or variation of returns on the same assets or market index can correctly quantify an asset's volatility. Market stability, short- and long-term expectations, and herding behavior effect HFT and volatility. According to several experts, HFT has exacerbated market volatility. HFT's liquidity and spread benefits are broadly accepted, but its price volatility cost is contested. To affect stock prices, portfolio managers and traders require smarter brokers like quantitative brokers. Investors and traders can assess market conditions using this study.

Methodology:

This is an analytical study where the researcher has taken secondary data with a sample of top 10 stocks based on market capitalisation from BSE for a period of 3 months (one contract period). The data is analyzed the data with Ordinary Least Squares (OLS) method to estimate the parameters. Large degrees of multi-collinearity among independent variables do not affect the unbiasedness of the ordinary least squares (OLS) estimator. Furthermore, the OLS estimator becomes biased when an important variable is removed from the model, leading to unstable estimates for the regression coefficients.

Outcome of the Study:

The analysis is going to prove that HFT has an impact on the volatility of the selected firms. The impact of this study would help the policy makers and the intermediaries that using of the updated HFT in stock markets will affect the volatility. This would in turn increase the volume of trading by attracting more investors into the markets.

Originality of the study:

The research study is original in nature and never carried out before in stock markets exclusively in BSE. Even though previous studies were carried out with reference to NSE, this study primarily tests whether HFT impacts on BSE stock market which is the largest stock exchange in India.

Key words: High Frequency Trading, Algo Trading, Stock Markets, Volatility

Declaration: The authors declare that this study is not sent for any publication earlier.

1. Introduction

Investors have always needed faster access to and processing of fresh data, as well as the transmission of electronic signals detailing financial choices to the market, in order to retain a competitive edge. Although while the time lag between an action taken by one market player and another might be as little as a few seconds, milliseconds, or even microseconds, it is nevertheless lengthy enough to have a significant impact on how wealth is distributed in the financial markets. In the last two decades, major technological developments have enabled much faster trading across most financial markets. The new market structure not only made it easier for everyone to take part, but it also paved the way for a completely novel kind of trading called high frequency trading (HFT). (i) large numbers of submitted electronic messages (and orders), (ii) low latency, and (iii) the search for intraday profits defines high-frequency trading (HFT). Due to the very small lag times between transactions, HFT may be thought of as a subset of algorithmic trading (AT). The main difference is that HFT requires low latency action.

In the new millennium, high-frequency trading (HFT) became an increasingly important aspect of the financial markets' entire trading process. It has been shown that in a sample of NASDAQ equities from 2008-2009, 26 HFT companies accounted for as much as 74% of the total trading volume(Brogaard et al., n.d.). In 2012, HFT is expected to account for 51% of the market share in the United States (*High-Frequency-Trading*, n.d.). Thirty-one high-frequency trading (HFT) companies accounted for 46 per cent of all activity on the Canadian stock exchange in 2010-2011(Boehmer, Li, and Saar 2018). In 2009, HFT was predicted to account for up to 40% of all trading in the European market (Grant & Haldane, 2010). It was observed that between 25 and 50 percent of large-cap stock transactions in Sweden employed HFT in a comparable sample from 2011-2012 (Boehmer et al. 2018). More than 60% of all stock transactions in the United States were executed by HFT in 2016 (Bazzana and Collini 2020). High-frequency trading (HFT) has become the norm in the futures market, just as it has in the stock market (HFT).

HFT has altered the markets and has a wide range of effects on non-HFT market players; moreover, its percentage in established financial markets is relatively high. Hence, despite HFT's relatively recent inception, there is a large body of written material on the subject. Beginning in the early 2000s, a growing number of scholarly articles focused on HFT was published, with annual totals reaching 500 by 2010 and 2,000 by 2015. It's worth noting that most academic studies have focused on advanced economies. As HFT emerged significantly later and in smaller quantities in nations with less developed technology infrastructure and no market fragmentation or dark pools, few research have looked at HFT activity in developing markets (Haldane, Brennan, and Madouros 2010) (Qin and Zhu 2017) (Ersan and Ekinci 2016) (Ekinci and Ersan 2018) (Jia et al. 2023). This research aims to shed light on the many outstanding uncertainties surrounding HFT and its effect on Volatility. First, we describe the results of previous studies on the aggregate effects of HFT on Volatility, and then we address two aspects that play a significant role in the creation of inconsistent conclusions concerning the effects of HFT.

1.2. HFT and its relation to Volatility

High-frequency trading either stabilizes the market and even decreases volatility, or it has no effect on volatility at all. According to Brogaard, HFT does not add volatility and may even decrease it (Brogaard 2012). HFT reduces short-term volatility, according to (Hasbrouck and Saar 2013). Hagstromer and Norden make similar arguments, namely that market makers' high-frequency trading reduces volatility (Hagströmer and Nordén 2013). By doing extensive research into the forex market, Chaboud et al. argue that algorithmic trading actually reduces market volatility (Chaboud et al. 2014).

Conrad, Wahal, Xiang, and Hasbrouck all pay special attention to the ask and bid prices (Conrad, Wahal, and Xiang 2015). In the former, it is determined that the amount of quotation activity does not contribute to the degree of volatility. The latter group, however, claims that increased volatility is caused by HFT's rivalry. In contrast to the perspective of Bazzana and Collini, who believe that HFT has no effect on market volatility, aggressive HFT actually raises volatility whereas passive HFT lowers it (Bazzana and Collini 2020). Although the aforementioned works disagree on a number of points, they all agree that HFT has the potential to impact volatility. To that end, we focused on the effects of HFT on volatility for our analysis.

2. Review of Literature

Clapham, B., Haferkorn, M., & Zimmermann, K. (2023), technical issue with this exchange's infrastructure that inhibits high-frequency traders from making low-latency trades was looked at. This is a once-in-a-lifetime chance to examine how high-frequency trading affects the stock market. High-frequency trading is disrupted with significant effects on liquidity and, to a lesser extent, price volatility, but the analysis demonstrates that the impact on trading volume and number of deals is minimal. Investments in high-frequency trading technologies improve the quality of securities markets and so have a favorable effect on the economy as a whole by lowering transaction costs for all market participants (Clapham, Haferkorn, and Zimmermann 2023).

Ben Ammar, I., & Hellara, S. (2022)., Analyze how HFT affects the price swings of equities listed on the Euronext exchange. Increased HFT activity is correlated with less stock price volatility during times of calm trading. However, during intraday falls, HFT algorithms interact rapidly, causing high-frequency traders to pull back from the limit order book in large numbers. During these times, stock price volatility is elevated because high-frequency traders make aggressive trades and absorb more liquidity than they provide (Ben Ammar and Hellara 2022).

Meng, K., Li, S., & Cooper, R. (2022)., investigated the correlation between high-frequency trading and price swings. Despite the lack of consensus among the extant studies on this topic, they all agree that HFT has an effect on volatility. Our model makes use of historical trading data to make predictions about future market behavior. Using the VIXY exchange-traded fund (ETF), which tracks the performance of the VIX index, we discover that the ask side of high-frequency trading activity has significantly more meaningful predictability for both the level and return of VIXY, whereas the bid side appears to be negligible(Meng, Li, and Cooper 2022). Using data from stock exchange communications, Aquilina, Budish, and O'neill determined the "latency arbitrage" of high-frequency trading (2022). Twenty percent of FTSE 100 share trading volume is due to latency arbitrage races, which occur once every minute per symbol. There is a $5 billion annual stake in only the global equities markets, and races account for almost a third of price impact and the effective spread (important microstructure indicators of the cost of liquidity). Latency arbitrage imposes an approximately 0.5 basis point penalty on trade (Matteo Aquilina, 10 September 2021).

Andersen, T., et.al. (2021), presents an overview of the Options Price Reporting Authority's (OPRA) high-frequency option trade and quote data. They provide a thorough introduction to the U.S. option market, covering everything from market legislation to the trading procedures used by each of the 16 option exchanges that make up the market. The authors have surveyed the literature that makes use of high-frequency options data, provided an overview of the OPRA dataset's general structure, and provided a detailed empirical description of the observed option trades and quotes for a subset of underlying assets in a dataset containing over 25 billion records. They looked for different kinds of anomalous data and gave advice on how to clean it up. Two empirical applications, option-implied variance estimation and risk-neutral density estimation, are used to demonstrate the value of the high-frequency option data. The significant information content of the OPRA data is highlighted in both applications (Andersen et al. 2021).

Li, Y., Nolte, I., & Nolte, S. (2021)., created a time-dependent transition probability Markov-Switching Autoregressive Conditional Intensity (MS-ACI) model and demonstrated that it can be accurately predicted using the Stochastic Approximation Expectation-Maximization technique. Using our model to analyze high-frequency transaction data, we find two intraday volatility regimes: a dominant regime that is present throughout the trading day and represents investors' risk-transferring trading activity, and a minor regime that is concentrated around market liquidity shocks and primarily captures the impacts of firm-specific news arrivals (Torben G Andersen, 2021/1/6).

Yagi, I., Masuda, Y., & Mizuta, T. (2020)., agents-based simulations were used to examine the primary liquidity metrics in a simulated market with and without HFT participation. All liquidity metrics in markets with HFT participation improved more than those in markets without HFT participation, the research revealed. We also showed that market liquidity may be evaluated not only by the primary liquidity measures, but also by execution rate, after looking into the relationships between these indicators in our simulations and the existing empirical literature. Hence, it is proposed that in future research, the execution rate might be a suitable innovative liquidity indicator (Yagi, Masuda, and Mizuta 2020).

Ben Ammar, I., Hellara, S., & Ghadhab, I. (2020)., examines the effect of HFT on the intraday liquidity of CAC40 equities traded on Euronext. We find substantial evidence, via the generalized technique of moments estimator, that higher levels of HFT are linked to narrower spreads and deeper pools of liquidity. HFT improves liquidity because the adverse selection costs caused by knowledge asymmetry between market players are reduced (Ben Ammar, Hellara, and Ghadhab 2020).

Heng, P., Niblock, S. J., Harrison, J. L., & Hu, H. (2020)., analyzes the capacity of the Australian futures market to absorb information after large planned macroeconomic releases and the colocation of high-frequency trading (HFT) facilities in that market. For all four futures contracts studied, the study found that trading activity and liquidity improved once HFT facilities were co-located. Furthermore, the four futures contracts show the market's ability to quickly process and react to news of significance (Heng et al. 2020).

Virgilio, G. P. M. (2019)., examined how high-frequency trading impacts market performance metrics such volatility, transaction costs, liquidity, price discovery, penalizing slower traders, and flash crashes. Although, as is common in the financial sector, there are conflicting opinions, no agreement has been reached on the worth of most criteria. Finally, this study analyzes the drop in high-frequency traders' earnings that has been so widely criticized in the media (Virgilio 2019).

Chung, K. H., & Chuwonganant, C. (2018)., established that stock market swings have an effect on stock returns both immediately and over the long-term through affecting liquidity. Stock gains are diminished when market volatility raises risk and illiquidity premiums. With U.S. market regulatory changes that increased competition between public traders and market makers, decreased tick size, and diminished the role of market makers, it is not surprising that stock returns are more sensitive to volatility shocks in the high-frequency trading period (Chung and Chuwonganant 2018).

Brogaard, J. (2012)., looked into how HFT works and how it affects price fluctuations. This research demonstrates a link between HFT and volatility. As stock-specific volatility rises, HFTrs' activity shifts, with the direction of the shift differing dramatically across liquidity providers and liquidity takers. In a similar vein, the outcomes shift depending on the length of the observational window. I employ a Granger causality test to see if there is a statistically significant link between HFT and volatility. Granger causation can be shown in both directions, with significant evidence linking volatility to HFT activity and vice versa. Stock-specific news and volatility are found to increase the extent to which HFTrs supply liquidity while decrease the extent to which HFTrs take liquidity. In contrast, macro news tends to be negative(Brogaard 2012).

3. Objective:

The main objective of this paper is to study the impact of the HFT on volatility of the selected stocks in BSE market.

4. Hypothesis:

H_0: There no significant impact of HFT on Volatility of the stocks.

5. Data collection and Methodology

This is an analytical study where the researcher has taken secondary data with a sample of top 10 stocks based on market capitalisation from BSE for a period of 3 months (one contract period). The data set covers the time period of April 2022 - July 2022. Out of ten select stocks the researcher is unable to get sufficient data for three stocks namely SBI, BHARTHI AIRTEL and COAL-INDIA. So, this study has covered only seven stocks namely POWER GRID, TATA, ITC, AXIS, ONGC, NTPC, and ICICI. Stock price data, trading volume, and number of transactions on minute basis are collected using Refinitiv data source. Stocks are included in the sample if there are at least 3 monthly observations. There were 23236 records in each stock which was covered from April 2022 - July 2022. We track the unpredictability of the market and the volatility of specific stocks. The Data is analysed with descriptive statistics and multiple regression analysis (Least Square Method)

6. Data Analysis:

In this section, the researchers are tried to know the basic characteristics the data. So, here the standard deviations and volatilities for all the select companies "POWER_GRID, TATA, ITC, AXIS, ONGC, NTPC, ICICI". Variance will tell us spread of the data and volatility will explain the changes in the share prices.

Table-1: Descriptive Statistics

Company	N	Std. Deviation	Volatility (152.43)
ONGC	23236	14.63932	2230.05
NTPC	23236	7.75936	1181.33
ITC	23236	9.40706	1432.84
TATA	23236	16.90787	2576.06
ICICI	23236	25.20267	3841.23
AXIS	23236	52.85874	8055.92
POWER_GRID	23236	9.60362	1463.32

The volatility of a stock is measured by looking at the standard deviation of its annualized returns over a certain time frame. Investing in a stock with high volatility means you can expect significant price swings between highs and lows over a short period of time. Considering the data shown above, we can deduce that AXIS bank has the greatest degree of volatility among the listed corporations. Thus, AXIS bank shares experience more volatility than those of certain other well-chosen corporations.

Multiple regression of High frequency trading on the volatility of BSE

The purpose of this section was to determine which firm among those chosen by the researcher saw more fluctuations in BSE.

Table 2 shows the model used to fit the association between the dependent variable and the independent variables.

Dependent Variable: Volatility

Independent variables: Share prices of select companies

Table-2: Showing the Regression Model for Volatility of the select companies of BSE

Model	R	R square	Adjusted R Square	F-value	the p-value

1	.932[a]	.869	.869	22091.370	0.00 **

a. Predictors: (Constant), Volatility
b. Dependent Variable: POWER_GRID, TATA, ITC, AXIS, ONGC, NTPC, ICICI

In the table, you can see a summary of the regression model. In order to measure how well a model fits data, the R-Square statistic is often used. R^2 = 1 minus the ratio of residual variability. The coefficient of multiple determinations (R^2) accounts for the degree to which the independent variables contribute to explaining the variation in the dependent variable. Data analysis reveals that the predictor variables, taken together, explain 86.9% of the variance in volatility.

Volatility of the shares was found to have the potential to predict the changes (R^2 = 0.932). The R^2 value in this model indicates that volatility account for 86.9% of the observed variability in performance levels. The remaining 13.1% is unaccounted for the changes in the price of the share. This variation is due to additional factors not included in the model. The F value (F= 22091.37 and P 0.00) indicates that this variation is extremely significant.

Table-3: Showing Unstandardized and Standardized Coefficient Values of Volatility

It gives the specifics of the model parameters (the beta values) as well as their relevance. It reveals that b0 was the Y-intercept and that this is the constant's value B. So, according to the table, b0 is -7894.9, which means that when no predictors exist (when X=0), the model predicts that the decrease in the price values. The value of b1= 2.975 indicates that increasing 1 unit of perception increases total volatility by 2.975 times. Other variables' b values are -63.53, 5.718, and so on.

Model	Unstandardized Coefficients		standardized Coefficients	t-value	p-value
	B	Std. Error	Beta		
(Constant)	-7894.970	125.719		-62.799	.00*
ONGC	2.975	.365	.048	8.149	.00*
NTPC	-63.535	.773	-.540	-82.207	.00*
ITC	5.718	.366	.059	15.626	.00*
TATA	-2.009	.254	-.037	-7.917	.00*
ICICI	-8.694	.255	-.240	-34.097	.00*
AXIS	20.207	.103	1.171	195.508	.00*
POWER_GRID	56.087	.400	.590	140.172	.00*

It is understood that the major factors that, in ONGC when there is change in the value of BSE index then there will be some positive increase in the share value of ONGC; similarly, there is change in the value of BSE index then there will be some decrease in the share value of the NTPC price and is high in the change in terms of decrease. It observed that, there existed best increase in the value of power grid when there is some change in the BSE.

7. Conclusion:

The volatility of a stock is measured by looking at the standard deviation of its annualized returns over a certain time frame. Investing in a stock with high volatility means you can expect significant price swings between highs and lows over a short period of time. According to the data AXIS bank is having the highest volatility compared to other select companies. So, there is more fluctuations in the price of AXIS bank shares compared to other select companies. and NTPC is less influencing with BSE. From the results of the multiple regression analysis, it also understands that ONGC when there is change in the value of BSE index then there will be some positive increase in the share value of ONGC; similarly, there is change in the value of BSE index then there will be some decrease in the share value of the NTPC price and is high in the change in terms of decrease. All the selected companies are fluctuating according to the BSE. But, ONGC, ITC, AXIS Bank and power grid are influencing positively; NTPC, TATA, ICICI are influencing negatively. It is concluded that HFT is significantly Affected the volatility of the stocks of BSE.

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